

# Bitcoin (BTC) Price: A Predictive Analysis

Springboard - DSC | Capstone Project 2

By John Arancio

Can BTCs next day  
closing price be  
accurately predicted?

฿ Price action lacks understanding

- Dramatic speculation
- Lack of empirical reasoning

฿ Volatility

- High risk

฿ Influx of institutional investment/interest

- Grayscale Trust (owns 3.9% of circulating BTC)
- Goldman Sachs (61% of clients expect to increase exposure to cryptocurrency)

# Approach

## ฿ Binance API client (historical daily prices)

[09/02/2019 - 11/15/2020]

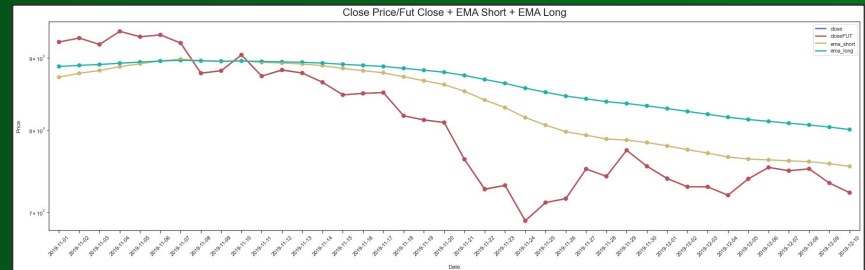
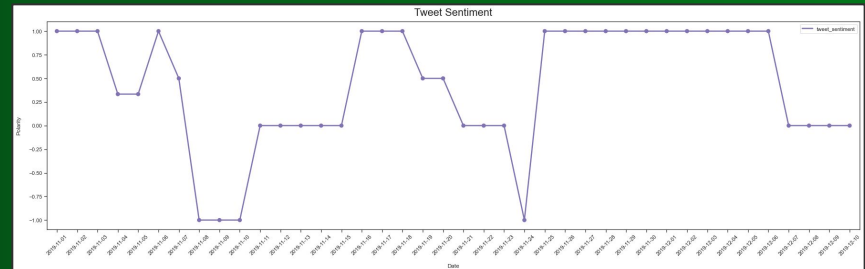
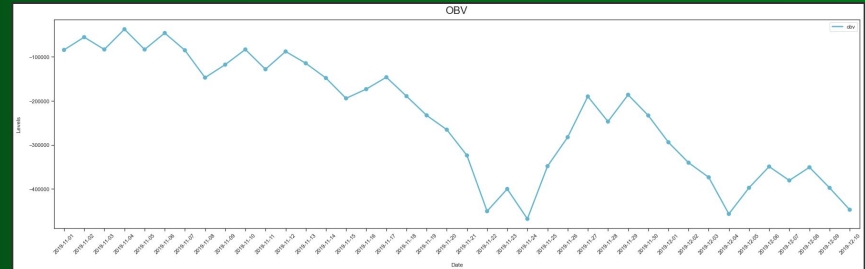
- Range: \$10,340 - \$15,957 (+54%)
- Low: \$4,800
- High: \$16,320.70
- Avg. Price: \$9,367.31

## ฿ Indicators as potential features

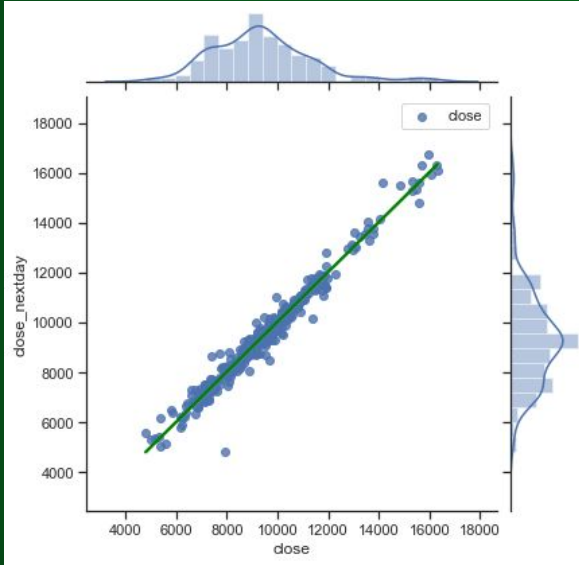
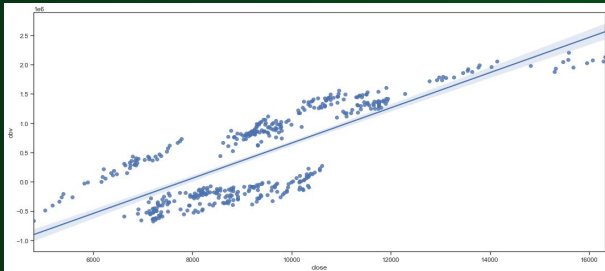
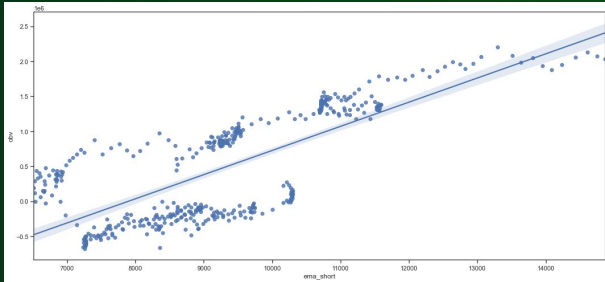
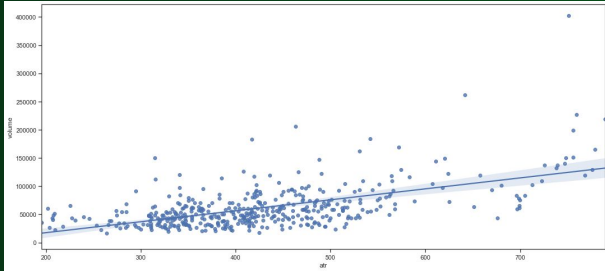
- EMA Long/Short, ATR, OBV
- Total indicators analyzed: 6

## ฿ Tweet sentiment via historical web scrape

- Avg. sentiment per day (mean polarity)
  - Bullish (positive) tweet = 1
  - Neutral tweet = 0
  - Bearish (negative) tweet = -1



# Approach



Exploratory Data Analysis  
and  
Feature Selection

- ⌘ Variable multicollinearity
  - Volume/ATR
  - OBV/EMA Short
  - OBV/Close
- ⌘ Correlation to target
  - Highest linear correlation
    - Close
    - EMA Long/Short
    - OBV
    - Volume
    - ATR
    - Tweet Sentiment

# Modeling

## Five distinct models

- Ordinary Least Squares (OLS)
- Lasso
- Ridge
- Random Forest Regression (RFR)
- Long Short Term Memory (LSTM)

Linear  
Regression

Ensemble Regression  
(Decision Tree)

Recurrent Neural  
Network (RNN)

## Model Tuning

- Regression Pipeline
  - GridsearchCV
- RNN
  - Hyperas

## Interpretation

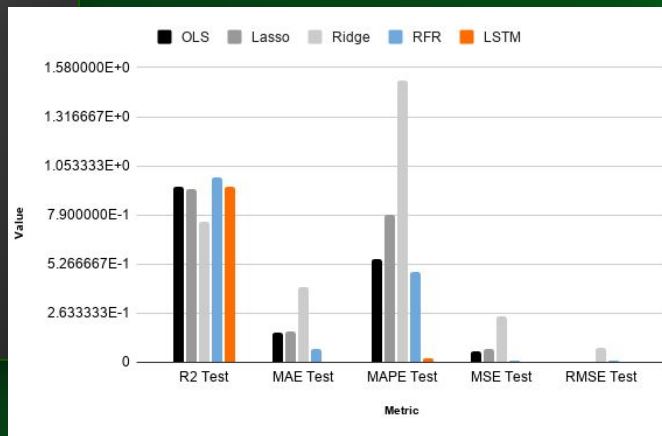
- LIME Explainer
- Residuals
- Coefficients
- Feature Importance

## Best Performance

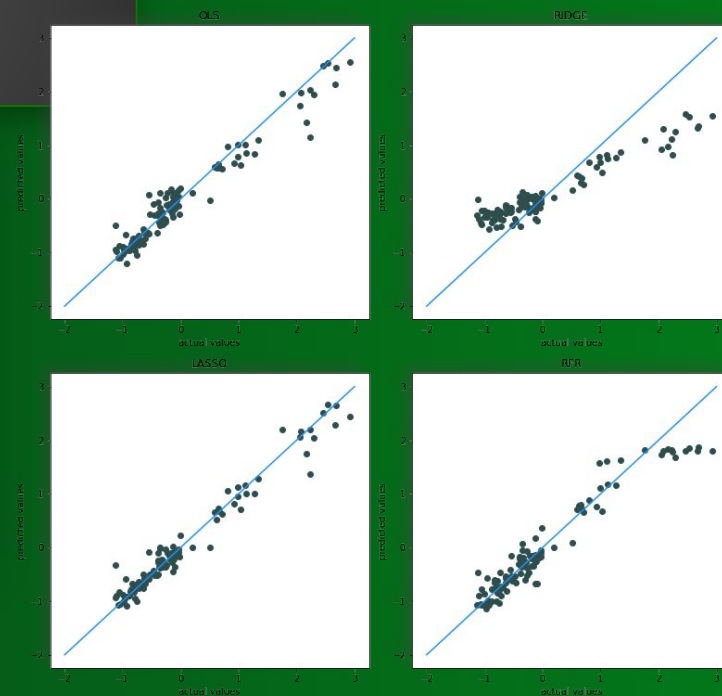
- Random Forest Regression (RFR)
- Long Short Term Memory (LSTM)

## Worst Performance

- Ridge

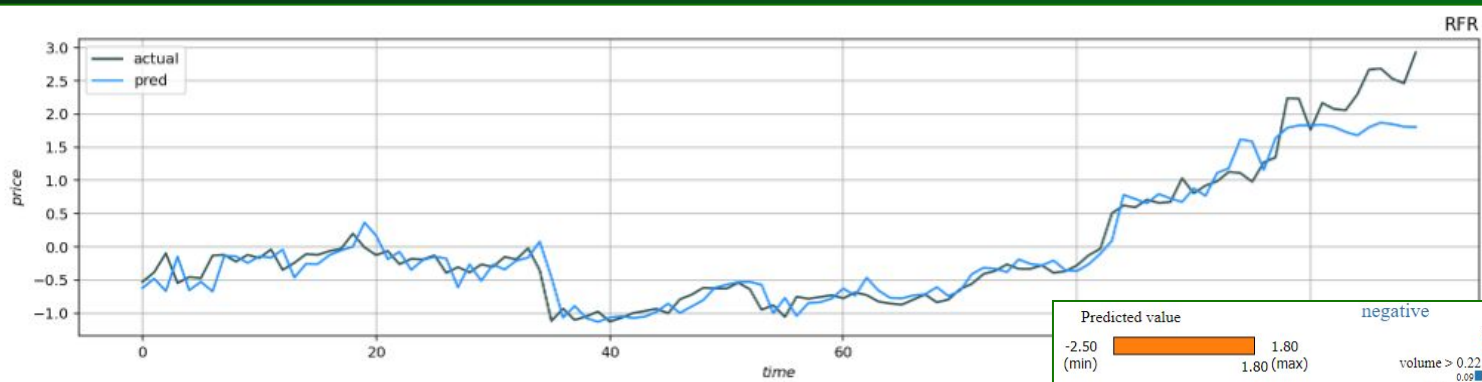


Regression Models Performance: Actual Vs Pred

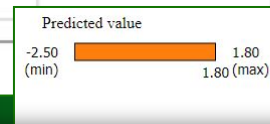


# Findings

(RFR Test Prediction)

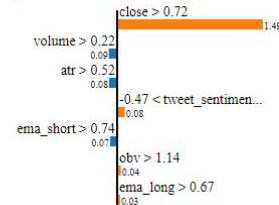


	R2 Test ▼	MAE Test	MAPE Test	MSE Test	RMSE Test	OOB Train
RFR	0.98845	0.06853	0.48569	0.01176	0.00686	0.91361



negative

positive



Feature Value

close	2.35
volume	2.72
ema_short	1.91
ema_long	1.77
atr	1.77
obv	2.20
tweet_sentimen...	-0.24

	Importance
1 close	0.924208
2 atr	0.028656
3 obv	0.013587
4 ema_long	0.013533
5 volume	0.011165
6 ema_short	0.00675

## Scores

- Highest R2
- Lowest MAE, MSE, RMSE
- Valid OOB

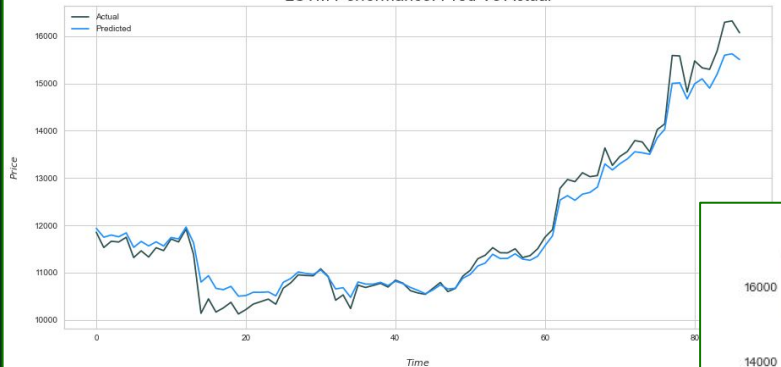
## Interpretation

- Close HEAVILY weighted
- Other features minimally weighted

# Findings

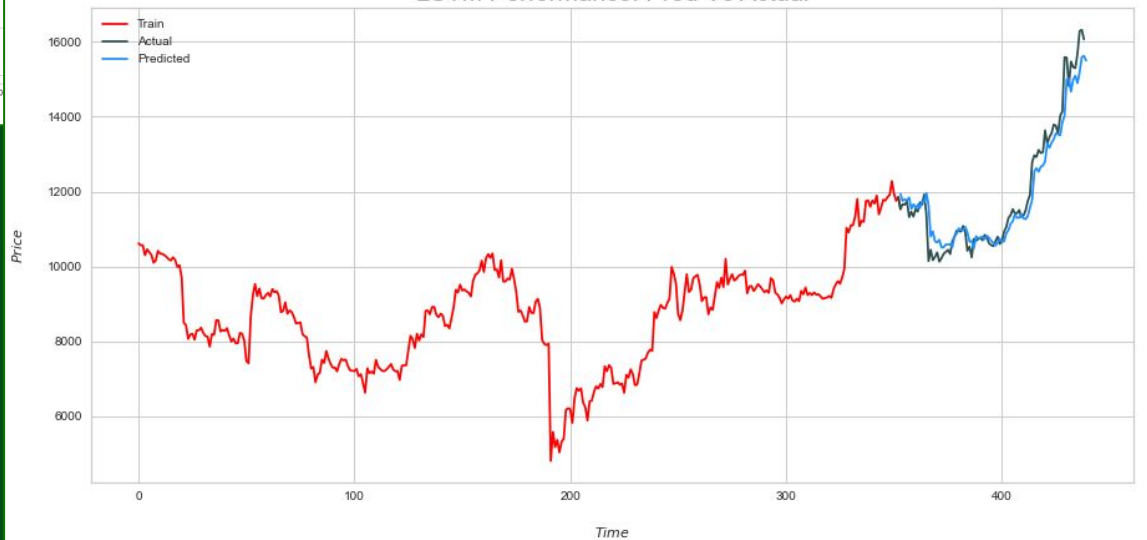
(LSTM Test Prediction)

LSTM Performance: Pred Vs Actual



	R2 Test ▲	MAE Test	MAPE Test	MSE Test	RMSE Test
LSTM	0.9395	304.9840	0.0247	180,906.31	425.3308

LSTM Performance: Pred Vs Actual



## ⌘ Scores

- Second highest R2
- Lowest MAPE
- MAE = approx. \$305 avg difference

## ⌘ Residuals

- Greatest positive: 1,129.17
- Greatest negative: -1,730.21

# Conclusions

## ⌘ Volatility handled well by RFR and LSTM

- Volume momentum plays big role in BTC price action (OBV)
- ATR useful with RFR

## ⌘ LSTM creates dynamic S&R (support and resistance) line, similar to a EMA/MA

## ⌘ Models generate confluence for potential signals

- Risk reduction

## ⌘ Standard asset indicators/metrics (i.e. open, close, volume) more important than extra indicators

## Further Work

- Perform deeper analysis into Tweet sentiment
- Train/test models on more data
- Fine tune the hyperparameters of models
- Perform EDA with other indicators
- Implement signal generator
  - Back test
  - Compute Sharpe Ratio
- Test for replicable results on different assets (equities, ETFs, etc.)



# Recommendations

- ⌘ Use RFR and LSTM greatest positive and negative residual values to adjust model
- ⌘ Use top performing models as a signal generator in conjunction with own due diligence
- ⌘ Implement automated strategy to run LSTM as its own “advisor” or “HF trader”
- ⌘ Use findings to improve previous analysis or speculation for identifying potential volatile spikes